Optimal Firm Size and the Growth of Conglomerate and Single-Industry Firms

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Comments Welcome

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Abstract

We develop a profit-maximizing neoclassical model of optimal firm size and growth across different industries based on differences in industry fundamentals and firm productivity. The model predicts how conglomerate firms will allocate resources across divisions over the business cycle and how their responses to industry shocks will differ from those of single-segment firms. We test our model and find that growth of conglomerate and single-segment firms is related to fundamental industry factors and individual firm-segment productivity suggested by our simple neoclassical theory. Conglomerates grow less in a particular segment if their other segments are more productive and if their other segments experience a larger positive demand shock. We find that the growth rates of peripheral segments are very sensitive to relative productivity and that conglomerates sharply cut the growth of unproductive peripheral segments. We do find some evidence consistent with agency problems for conglomerate firms that are broken up. However, the majority of conglomerate firms exhibit growth across business segments that is consistent with optimal behavior.

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Several recent academic papers and the business press claim that conglomerate firms destroy value and do a poor job of investing across business segments.[1] Explanations for this underperformance share the idea that there is an imperfection either in firm governance (agency theory) or in financial markets (incorrect valuation of firm industry segments). These studies implicitly assume that the conglomerates and single-industry firms possess similar ability to compete, and that they differ mainly in that conglomerates have chosen to operate in more than one industry. However, firms do differ in their ability to exploit market opportunities.[2] In the absence of a benchmark model of how these differences affect firms' to invest in different divisions, it is not clear whether earlier studies' results are driven by the underlying comparative advantages of different types of firms or by one or more of the postulated explanations.

In our paper, we analyze how firms grow across industries and at different stages of the business cycle in the absence of market imperfections, using a neoclassical model based on Lucas (1978).[3] We test the model by examining the growth and efficiency of over 50,000 firms and their business segments using plant-level data for the period 1975 to 1992. By using this plant-level data we can determine how the growth of a multiple-segment firm depends on each segment's efficiency, the returns-to-scale in the industries in which the firm operates, and demand shocks.

The model we develop here shows that firms with a comparative advantage, arising from managerial skill in producing within an industry, have higher growth and attain a larger size in that industry. As a firm's returns within an industry diminish, the firm limits its growth within the industry and moves into other industries. The optimal number and size of industry segments a firm operates depends on its comparative advantage across industries. Firms

[1] Lang and Stulz (1994), Berger and Ofek (1995) and Comment and Jarrell (1995) document a conglomerate discount in the stock market and low returns to conglomerate firms. Rajan, Servaes, and Zingales (1997) and Scharfstein (1997) examine conglomerate investment across different business segments. Lamont (1997) and Shin and Stulz (1997) examine the relation of investment to cash flow for conglomerate industry segments.

[2] Peters and Waterman (1982), Schmalensee (1985), and many other authors, have noted that firms differ even within the same markets. Lang and Stulz (1994) note that firms that become conglomerates may differ from those that stay within one industry. We discuss their attempt to control for these potential differences below.

[3] Firm growth has been examined in other contexts by Evans (1987) and Hall (1987). They test whether the relationship between firm growth and firm size is constant for different types of firms, as predicted by Gibrat's Law.

that are very productive in a specific industry have higher opportunity costs of diversifying. Thus, in equilibrium, if a high level of managerial skill is industry specific, single-segment firms are more productive than conglomerates in the same industries. If managerial skill is not industry specific, conglomerates may be more productive then single-segment firms. Comparative advantage also implies that the larger divisions of conglomerates are relatively more efficient than their smaller divisions.[4]

In the model the optimal growth of firms depends on their relative productivity. The same positive shock that causes more productive firms to invest and increase their market share can cause less productive firms to contract. Thus, inefficient and efficient firms should optimally invest differently when industry conditions change. This result implies that empirical tests of how conglomerates invest in response to changes in industry prospects could be misspecified if they do not control for the productivity of the firm's individual divisions.

The model also predicts that the effect of demand shocks on the growth of a conglomerate's division depends returns-to-scale in that division's industry, and in the other industries in which the conglomerate operates. Demand shocks in industries where returns-to-scale are decreasing have a smaller effect on the growth, both of the division that operates in that industry, and also of the conglomerate's other divisions.

A key prediction of the model is that demand shocks faced by a segment of a conglomerate firm affect the growth rates of other segments, and do so even in the absence of agency costs and financial market imperfections. If a division is less (more) productive than single-segment firms in its industry, a positive demand shock in one division increases (decreases) the growth rates of other segments. Because models that postulate an important role for agency costs and internal capital markets imply a different relation, this prediction can be used to distinguish empirically between these models and our neoclassical model.

Our empirical analysis shows that conglomerate firms are less productive than single-segment firms of a similar size. This provides and explanation for the finding of a conglomerate discount by Lang and Stulz (1994) and Berger and Ofek (1995). However, we argue that this difference of productivity is consistent with optimal behavior of firms when there are decreasing returns-to-scale and managerial skills have an industry-specific component.

The comparison of productivity within conglomerates exhibits two strong empirical regularities. Larger segments are more productive than smaller segments. This is consistent

[4]Our model analyzes how comparative advantage in the product market may leads some firms to become conglomerates. Models that predict that firms become conglomerates to benefit from more efficient capital allocation include Matsusaka and Nanda (1996), Stein (1997) and Fluck and Lynch (1996). Hubbard and Palia (1998) present evidence from the 1960s that is consistent with these models. Hadlock, Ryngaert, and Thomas (1998) provide more recent evidence consistent with a capital allocation benefit of conglomerates.

with maximizing behavior. The differences in productivity across segments also suggest that for most firms managerial talent has an industry-specific component. However, when divisions within a conglomerate are ranked by size, and compared with equally ranked divisions of other conglomerates, we find a positive relation between the segment's productivity and the number of industries in which the conglomerates operate. This suggests that those conglomerates that operate in many segments have a higher level of general ability than conglomerates that operate in a few segments.

While these comparisons of the productivities within conglomerate firms are consistent with a neoclassical model, they might also occur if conglomerates suboptimally expand into industries in which they have a low level of specific skill. To discriminate between these two possibilities, we examine how conglomerates grow in different industries. We test both whether the growth rate of a division is related to the efficiency of the conglomerate's divisions and how growth changes in response to industry shocks. The latter test permits us to test our model's predicted relation between growth and the segment's relative productivity against the relation implied by agency theories that predict suboptimal expansion into other industries.

The empirical tests show that the growth of both more- and less-productive firm segments is related to efficiency and fundamental industry factors, both for recession and expansion periods over the business cycle. Conglomerate firms concentrate their growth in their most productive industry segments. Divisions of conglomerates grow more slowly if the conglomerates other divisions are efficient in their industries, and faster if the other divisions are inefficient. The growth of peripheral divisions, in particular, is strongly related to their productivity.[5]

Changes in a segment's growth rate in response to industry shocks in other segments are consistent with the neo-classical model. If a conglomerate's industry segment is less productive compared with other firms in its industry, a positive demand shock in that division industry increases the growth rates of the conglomerates' other segments. Conglomerates grow less in a particular segment if their other segment(s) is more productive and experiences a larger positive demand shock and if their other segment is in a high-returns-to-scale industry. This evidence is not consistent with the hypothesis that conglomerates expand unproductive industry segments or protect them from recessions by using cash flows from

[5]This high sensitivity of peripheral-segment growth to productivity is also consistent with a capital allocation motive for conglomerates. Conglomerates my be experimenting by entering new industries. If the they proce to have a comparative advantage in that industry they expand, otherwise they contract their operations.

other divisions.

We do find some evidence to indicate that some conglomerates may have agency problems. We examine conglomerates that are broken up into single-segment firms during the 1980s.[6] We find that the growth of these broken-up conglomerates is not consistent with our model of optimal growth. However, even for these firms, we find no evidence that conglomerates subsidize the growth of inefficient divisions. We also find that the growth rates of firms that remain conglomerates, which are the majority of conglomerates, are strongly sensitive to industry variables and productivity. These findings are consistent with optimal behavior. The results indicate that the surviving conglomerates grow efficiently across their business segments.

Our work follows prior papers by Lang and Stulz (1994) and Berger and Ofek (1995), who show that conglomerate firms have a discount in the stock market relative to single-segment firms. Comment and Jarrell (1995) document that stock market returns to conglomerate firms are lower. Berger and Ofek (1995) and Comment and Jarrell (1995) explain their findings by appealing to agency theories that predict a misallocation of capital as firms allocate capital to divisions that are under-performing. Lang and Stulz (1994) note that poorly performing firms may choose to become conglomerates. However, they find only limited evidence for this hypothesis, and their data does not permit them to examine how productivity varies by segment. Rajan, Servaes, and Zingales (1997) and Scharfstein (1997) examine how investment decisions are related to industry Tobin's q. Using data from 1979, Scharfstein finds that conglomerate firms invest more in low-q industries. Rajan, Servaes, and Zingales also find that the extent of firm investment in divisions in low-q industries is related to the diversity of investment opportunities across divisions.

Our analysis differs from earlier work on conglomerate firms. Our model gives a benchmark for what growth should be, based on optimal firm size. We can measure efficiency at the plant level. Thus, we can show that in certain instances, seemingly inefficient behavior by conglomerates is consistent with profit maximizing. In particular, we show that when firms' comparative advantage is taken into account, it can be optimal for less-efficient firms, when their industry experiences a positive demand shock, to invest outside of their industry. Thus, the observation that conglomerates invest less in their main segments than do single-segment firms when industry prospects improve, does not imply that there are market imperfections that cause conglomerates to lose value.

The paper is organized as follows. Our framework is discussed in Section I. We discuss

[6]See Lang, Poulsen, and Stulz (1995), Comment and Jarrell (1995), and Berger and Ofek (1997) for an analysis of the recent increases in firm restructuring.

data and our methodology in Section II. Section III presents our results on growth and segment productivity for multiple-segment conglomerate and single-industry firms. Section IV concludes the paper.

I. Optimal Firm Size and Growth over the Business Cycle

We model firm growth in a setting which allows firms to differ in their ability to realize revenues from operating plants. This differing ability arises from managerial talent which varies across firms.[7] As in Lucas (1978), managerial talent is a scarce resource and firm size within an industry adjusts to economize on managerial talent.[8] Moreover, the extent to which managerial talent is industry-specific or can be applied in different industries determines whether or not firms should become conglomerates.

Consider two specific cases. First, talent is industry-specific and firms that expand beyond their best industry incur a penalty in form of lower productivity in the other industries. As a result, firms that do have a special competency in an industry will be focused, whereas conglomerates will tend be less efficient firms whose managers are not the most talented in any one industry. Second, if talent in one industry is highly correlated with the ability to manage in other industries, conglomerates are more likely to be efficient firms whose managers have reached the point of diminishing returns in any single industry. Most of our predictions apply for either assumption about how managerial talent can be applied across industries. These two cases lead to different interpretations of the observed lower valuation for conglomerate firms in the stock market than for single-segment firms.

We also examine how the optimum size of a conglomerate's division changes in response to shocks to demand and other characteristics in its industry and in other industries. The model yields testable predictions on how optimal growth in different industries is affected both by the comparative advantage of the firm in each industry, and by changes in industry conditions. The predictions of our model differ from those of agency models. As a result, our model can be used to distinguish empirically between neoclassical and agency theories of conglomerate behavior.

A. The model

At all levels of managerial talent, firms face costs of supervision that increase with size. In determining their optimal growth, and whether to operate in more than one industry, firms trade-off marginal revenues against marginal costs. These trade-offs depend both on

[7] We interpret managerial talent broadly, including as talent the ability to manage a large organization.

[8] So, for example, if there are very few highly talented managers and many incompetent potential managers, there will be a few big firms and perhaps many very small firms. On the other hand, if managerial talent is evenly spread around, there will be many moderately sized firms firms.

each firm's productivity and on demand conditions in each industry.

We assume that there is a population of n firms that can operate in a maximum of two industries, we denote industry A and industry B, respectively. Some of the firms, which we term single-segment firms and denote by the superscript ss, can operate in only one industry i, where $i = A$ or B. Conglomerate firms (denoted by superscript c) have the option of operating in both industries.[9]

All firms are assumed to be price-takers and to produce a homogeneous output. The level of demand in each industry is a random variable. Firms are endowed with industry-specific homogeneous production capacity. There is one period and two dates: $t = 1, 2$.

At time $t = 1$, the firms learn the actual realization of the next period's level of demand in each industry. A market for capacity opens in which firms can trade capacity units at a price r. Firms have a choice of using all their capacity to produce; scrapping some capacity and obtaining a salvage value; selling some capacity and using the remainder to produce; or buying more capacity and producing. Capacity may be purchased from and sold to other firms operating in the same industry, or from sources outside the industry. We assume that the total amount of capacity employed by the industry is $K = \alpha + \beta r$. Thus, total amount of capacity is a reduced form, reflecting the addition of new capacity (for high levels of r) and sales for scrap (for low levels of r).[10]

Finally, at time $t = 2$, the firm realizes the cash flows. For simplicity, we assume that capacity has no salvage value at $t = 2$.

In order to focus on the effect of differences in efficiency between firms on their optimal capacity in each industry, we make three key assumptions:

A1. In each industry, we assume that some firms operate plants more or less efficiently than do other firms. The efficiency with which any given firm operates plants can differ across industries.

Specifically, in each industry in which they operate, firms can be either high and low quality. High-quality firms, denoted by H, produce more output per unit of capacity than do low-quality firms, denoted by L.

A2. We assume that as their size increases beyond an efficient minimum scale, the firms face increasing costs of supervision and management

Thus, we assume that any given manager will do a better job of managing a small firm than a large firm. In this we follow Coase (1937) and Lucas (1978) in assuming diseconomies

[9] Our results on conglomerates below pertain to c firms. The assumption that there also exist single-segment firms simplifies the algebra substantially without loss of generality.

[10] Thus, we assume that the supply of capacity is not perfectly elastic.

of scale within firms. Firms use the variable input, labor, together with capacity units, to produce output. As capacity increases beyond the minimum efficient scale, firms exhibit neoclassical decreasing returns-to-scale, so that their marginal costs increase with output.

For ease of exposition we assume that a firm that operates k_i units of capacity in industry i faces variable costs of $w_i k_i^2$ to operate each period, with w_i is a positive constant that captures the cost of labor and other inputs that all firms use. We also assume that all firms face an additional coordination cost that depends on the total capacity operated in both industries, $v(k_A + k_B)^2$.

A3. The level of output demand is random. When demand uncertainty is resolved, the price of capacity adjusts to clear the market.

To enable us to focus directly on the issues of interest, we assume that we also assume that the opportunity cost of capacity outside the two industries A and B is sufficiently low so that it is optimal for both high- and low-quality firms to operate for some feasible level of demand in both industries.

B. The first-best equilibrium in a single industry

We first analyze the relative growth rates and the flow of assets between differing productivity over the business cycle in a single industry. Accordingly, in this subsection we assume that all firms in the industry are single-segment firms of that can produce only in that industry and we drop all industry subscripts.

We consider a single industry consisting of firms that do not have operations outside the industry. Let H firms produce one unit of that industry's output per unit of capacity. L firms produce only $d < 1$ units of output per capacity unit. The proportion of firms that are H firms is λ, and the optimal number of capacity units operated by H and L firms is k^H and k^L, respectively.

To make explicit the role of demand shocks and the distribution of capacity units on firm growth, we describe the equilibrium in the market for output. The market price that the customers pay in industry for the output is determined as $p = a - bQ$, where Q is the aggregate output and b is a positive constant. The intercept a is a positive random variable. A positive shock occurs when the realization of a exceeds its expected value. A negative shock is defined analogously. We focus on the capacity flows that occur at time $t = 1$, when a is revealed.

Proposition 1 *If the supply of total capacity is not perfectly elastic, then in industries experience a positive (negative) demand shock, highly productive firms grow (decrease) in size relative to less productive firms.*

Proof

We obtain the output of high-quality firms by maximizing the firm's operating profit, $pk^H - rk^H - w\left(k^H\right)^2$. Solving for k^H, we obtain $\frac{p-r}{2w}$ as the optimal capacity that high-quality firms operate at the given opportunity cost, r. We obtain the capacity at which the low-quality firms operate is similarly obtained as $k^L = \frac{pd-r}{2w}$. Notice that $k^H > k^L$, so that a high quality firm uses more capacity than the low-quality firm at every price level.

If both H and L firms are active in the industry and the price of capacity exceeds its salvage value, the market price of the output is $p = a - bn(\lambda k^H + d(1-\lambda)k^L)$. We determine the price of capacity by equating the demand for capacity by each type of firm to the total number of capacity units available, either on the secondary market or as supplied by manufacturers, so that

$$\alpha + \beta r = \lambda n \frac{p-r}{2w} + (1-\lambda)n\frac{pd-r}{2w}. \tag{1}$$

The first term on the right hand side of the equation is the demand for capacity by the λn high-quality firms. The second term is the demand for capacity by the $(1-\lambda)n$ low-quality firms. Solving equation (1) for the opportunity cost of capacity, and taking into account salvage value, yields

$$r = \max\left[\frac{p\left(\lambda + d\left(1-\lambda\right)\right)}{n+2\beta w} - \frac{2w\alpha}{n+2\beta w}, s\right]. \tag{2}$$

We focus on the region in which the supply of capacity is not perfectly elastic, $r > s$. Substituting the expression for the rental cost of capital (2) into the expressions for the desired capacity by high- and low-quality firms, we obtain

$$k^H = \frac{\alpha}{n+2\beta w} + \frac{(1-d)(1-\lambda)n + 2\beta w}{2w(n+2\beta w)}p \text{ and } k^L = \frac{\alpha}{n+2\beta w} - \frac{(1-d)\lambda n - 2\beta dw}{2w(n+2\beta w)}p\,. \tag{3}$$

In this region, the derivative of the ratio (k^H/k^L) with respect to the output price, p, is

$$\frac{2(1-d)(n+2\beta w)wK}{\left(2w\alpha + (2\beta dw - (1-d)\lambda n)p\right)^2} > 0. \tag{4}$$

Thus, as p increases, the ratio k^H/k^L increases. Positive price shocks are associated with higher growth of high-quality firms relative to low-quality firms. Since positive shocks to a at time $t = 1$ translate into increases in p, it is straightforward, but messy, to show that the same relation obtains for the ratio k^H/k^L and a.

■

Proposition 1 characterizes how the sizes of efficient and inefficient firms vary in response to demand shocks. Because firms' average costs increase with size, there is an equilibrium distribution of firm size. In equilibrium, firms will increase their capacity until the marginal value of each capacity unit is the same in each firm. The optimal distribution of capacity depends on the value of the additional output that the high-quality firms can produce with each unit of capacity. At high levels of demand, as demand increases, the value of this additional output increases, and the high-quality firms in the industry will acquire additional capacity at a higher rate than low-quality firms.[11] This process continues until the increase in the value of output, which occurs when a unit of capacity is transferred from a low-quality to high-quality firm, exactly equals the net increase in the costs of supervision.

While we expect the total supply of capacity in the industry to be inelastic, it may be that when demand is very low the opportunity cost of capacity is a fixed salvage price. When demand is this low it is straightforward to modify the model to show that negative demand shocks cause low-quality firms to scrap additional capacity at a higher rate than high-quality firms. Hence, negative shocks cause high-quality firms shrink less than low-quality firms.[12] Positive demand shocks cause the price of capacity to exceed the fixed salvage value. When this occurs the case described in Proposition 1 again obtains, and high-quality firms grow relative to low quality firms. As a result, when demand is so low that the opportunity cost of capital equals a fixed salvage price, the behavior of firm growth rates may be more complex. Since the details of this case are not central to our empirical analysis, we do not pursue it further in this paper.

C. The first-best equilibrium with conglomerate firms

We now introduce another industry and allow some firms to be conglomerates. Because segments of a conglomerate share some costs, they introduces externalities in how capacity is allocated in an industry following a demand shock.

For the case of the conglomerate firm, the profit function is

$$p_A d_A k_A^c + p_B d_B k_B^c - r_A k_A^c - r_B k_B^c - w_A \left(k_A^c\right)^2 - w_B \left(k_B^c\right)^2 - v \left(k_A^c + k_B^c\right)^2 . \qquad (5)$$

In the conglomerate profit function we allow the conglomerate to have a differential productivity d_i, where $i = A$ or B in each industry If the conglomerate is more (less) efficient than

[11]This may occur through purchases of new capacity either from the manufacturer or from low-quality firms. Although we do not investigate this issue here, the latter obtains when the productivity differences between high- and low-quality firms are sufficiently great.

[12]Let the salvage price be s. Then $k^H = \frac{p-s}{2w}$ and $k^L = \frac{pd-s}{2w}$. The derivative of the ratio (k^H/k^L) with respect to the output price, p, is negative.

the corresponding single-sector firms, $d_i > (<)1$. Maximizing this expression for k_i^c yields the optimal output of the conglomerate in each of the industries in which it operates.

$$k_i^c = \frac{(d_i p_i - r_i)(v + w_j) - (d_j p_j - r_j)v}{2(w_i w_j + v(w_i + w_j))}, \tag{6}$$

for j not equal to i.

The proofs below are significantly simplified if we also assume that there exist some firms which are constrained to operate in one segment only.[13] The profit function of a single-segment firm that operates only in industry i is,

$$p_i k_i^{ss} - r_i k^{ss} - (w_i + \nu)(k_i^{ss})^2, \tag{7}$$

where we introduce a cost of management ν which is the same in both industries and we assume, without loss of generality, that single-segment firms produce one unit of output per unit of capacity. This yields an optimal output analogous to that in the single industry case, so that $k_i^{ss} = \frac{p_i - r_i}{2w_i + \nu}$.

Proposition 2 *Ceteris paribus, conglomerates produce more in those industries in which they are relative efficient than in industries in which they are less efficient.*

Proof

Let $d_A = d_B + \varepsilon$, where $\varepsilon > 0$. Then, all other things equal, the derivative of the ratio of a conglomerate's capacity in industry A to the capacity in industry B is

$$\frac{p_A(d_B p_B - r_B)(w_A w_B + v(w_A + w_B))}{((p_A(d_{B+}\varepsilon) - r_A)\nu - (d_B p_B - r_B)(v + w_A))^2}. \tag{8}$$

Thus ratio of capacities increases in ε as long as the firm operates in both industries, so that $d_B p_B - r_B > 0$. ■

The neoclassical model predicts that, *ceteris paribus*, a positive relation between the proportion of the conglomerate's output produced in an industry and the efficiency of the conglomerate in that industry. Thus, if a conglomerate's segments differ in size, the main segments are more efficient than the peripheral segments.

If managerial talent is industry specific, all firms produce most in industries where they are relatively more efficient, so that within each firm there is a positive relation between segment size and productivity. Firms that are highly productive in one industry are likely

[13]The proportion of these firms in each industry can be made very small without affecting the results derived below.

to be less productive in the other industry. For these firms, the difference between d_A and d_B is likely to be large. As a result, firms with highly talented managers are focused, with most of their production in one industry. Firms whose managers are not as highly skilled in any one industry are less focused.

By contrast, if managerial talent is not industry specific, so that $d_A = d_B$, all firms divide their production equally between the industries. In this case, there is no relation between productivity and focus, and there are no differences in productivity across segments. Larger firms, however, are more productive than smaller firms across all segments.

The model can yield predictions on how demand shocks in one industry affect the production of a conglomerate in its other industry. To make these predictions, we must specify the market equilibrium in both industries. To show this, we make several simplifying assumptions for tractability.

We assume that of the total number of firms n a fraction, λ_c, are conglomerates. Other firms are single-segment firms. An equal number of single-segment firms operates in both industries, so that the fraction of the n firms operating only industry i is λ_{ss}, where $\lambda_{ss} = (1-\lambda_c)/2$. Similarly, we assume that the capacity in each industry is fixed at K_i.

We also focus directly on price shocks in each industry; we do not trace out the relation between a demand shock and the subsequent price shock.[14] First, we analyze how price shocks in industry A on the output of a conglomerate in industry B.

Proposition 3 *If conglomerate segments in industry A are sufficiently less efficient than single-segment firms also operating in industry A ($d_A < \frac{n\lambda_{ss}}{n\lambda_{ss}+2\beta(\nu+w_j)}$), then a positive price shock in industry A results in an increase in growth rates of segments of conglomerates that operate in industry B relative to the growth rate of single-segment firms in industry B. If the conglomerate segments in industry A are more efficient than the single-segment firms in that industry ($d_A > \frac{n\lambda_{ss}}{n\lambda_{ss}+2\beta(\nu+w_j)}$), then a positive price shock in industry A decreases the growth rate of conglomerate segments in industry B relative to the growth rate of single-segment firms.*

Proof

By substituting for k_i^c and k_i^{ss} into the industry equilibrium conditions $\alpha + \beta r_i = (\lambda_c k_i^c + \lambda_{ss} k_i^{ss})n$, where $i = A$ or B, we can solve for the price of capital in each industry. Substituting r_A and r_B into the expressions for k_i^c and k_i^{ss}, we obtain

[14] Since the full specification introduces additional terms in the expressions below, but is not material for our arguments, we do not specify it in this section. The proof of Proposition 1 for the single-industry case shows how this can be done in the two-industry case.

$$\frac{\delta(k_i^c/k_i^{ss})}{\delta p_j} = -\left[\frac{2(\alpha+\beta p_i)\nu(n\lambda_{ss}+2\beta(\nu+w_j))\left(\Theta_1+\Theta_2+\Theta_3\right)}{\left(n^2\left(\Theta_4-\Theta_5\right)+2n\left(\alpha\Theta_6+(\Theta_7+\Theta_8)\beta\right)\right)^2}\right]\left(\frac{n\lambda_{ss}}{n\lambda_{ss}+2\beta(\nu+w_j)}-d_j\right), \tag{9}$$

where

$$\Theta_1 = 4\beta^2(\nu+w_i)^2(\nu+w_j)(w_iw_j+\nu(w_i+w_j)), \tag{10}$$

$$\Theta_2 = 2\beta n(2\nu+w_i+w_j)\left((1-2\lambda_{ss})\nu^2+(1-\lambda_{ss})(w_iw_j+\nu(w_i+w_j))\right), \tag{11}$$

$$\Theta_3 = n^2(1-2\lambda_{ss})\nu^2+(1-\lambda_{ss})^2(w_iw_j+\nu(w_i+w_j)), \tag{12}$$

$$\Theta_4 = (1-2\lambda_{ss})((1-d_i)p_i(1-\lambda_{ss})(v+w_j)+(1-d_j)p_j\lambda_{ss}v) \tag{13}$$

$$\Theta_5 = 4\beta(\alpha+\beta p_i)(v+w_j)(w_iw_j+\nu(w_i+w_j)) \tag{14}$$

$$\Theta_6 = (1-2\lambda_{ss})v^2+(1-\lambda_{ss})w_iw_j+v(w_i(1-\lambda_{ss})+(2-3\lambda_{ss})w_j \tag{15}$$

$$\Theta_7 = d_jp_j(1-2\lambda_{ss})v(w_i+w_j)-p_i((2-d_i)(1-2\lambda_{ss})v^2 \tag{16}$$

$$\Theta_8 = w_j(w_i(1-\lambda_{ss})+(1-d_i)(1-2\lambda_{ss})w_j-v((1-\lambda_{ss})+3-(d_i(1-2\lambda_{ss})-5\lambda_{ss})w_B \tag{17}$$

The term in the square brackets in equation (9) is positive for all feasible λ_{ss} ($\lambda_{ss} < 0.5$). Thus, for all sufficiently low d_j ($d_j < \frac{n\lambda_{ss}}{n\lambda_{ss}+2\beta(\nu+w_j)}$) the result follows. ■

When a positive demand shock occurs in industry A, relatively efficient firms increase their market share. Conglomerates that are sufficiently inefficient lose capacity to other firms in that industry.[15] This reduction in capacity reduces their control costs. As a result, they become more aggressive competitors in industry B, and grow relatively faster than do other firms in that industry. When conglomerates are relatively more efficient in industry A, a positive shock in that industry causes them to expand faster in that industry, their control costs increase, and they become relatively less aggressive competitors in industry B.

We develop predictions about the role of economies of scale in each industry on the transmission of shocks. For tractability, we only derive results for the case where the total capacity is fixed, so that $\beta \to 0$.

Corollary 1 *If conglomerate segments in industry A are less efficient than single-segment firms, then the effect of a price shock in industry A on the growth rates of single-segment firms in industry B is greater when there are significant diseconomies of scale in industry A or industry B* ($\frac{\delta^2 k_B^{ss}}{\delta p_A \delta w_i} > 0$, $i = A$ *or* B). *If conglomerate segments in industry A are more*

[15] Note that "sufficiently" depends on the elasticity of supply of capacity into the industry. If supply is fixed ($\beta = 0$), then it is sufficient that $d_j < 1$.

efficient than single-segment firms, the effect of a price shock in industry A on the growth rates of single-segment firms in industry B is smaller when there are significant diseconomies of scale in either industry.

Proof

Differentiating $\frac{\delta k_i^c}{\delta p_j}$ from equation (9) with respect to w_j, we can determine how the sensitivity of the output of single-segment firms in industry i to price shocks in industry j varies in the economies of scale in its industry

$$\left[\frac{\lambda_{ss}^2(1-\lambda_{ss})^2(w_i+v)v}{2\left(\lambda_c\nu^2+(1-\lambda_{ss})^2(w_iw_j+v(w_i+w_j))\right)^2}\right](1-d_j). \tag{18}$$

The expression (18) is positive, indicating that the changes in production in industry i in response to shocks in industry j are smaller as w_j increases. Since w_j measures decreasing returns to scale in industry j, this implies that the response in industry i to shocks in industry j is smaller when there are decreasing returns to scale in industry j.

Differentiating the expression (9) with respect to w_i yields

$$\left[\frac{\lambda_{ss}^2(1-\lambda_{ss})^2(w_j+v)v}{2\left(\lambda_c\nu^2+(1-\lambda_{ss})^2(w_iw_j+v(w_i+w_j))\right)^2}\right](1-d_j).$$

This expression is also positive, implying that the higher the returns-to-scale in industry i, the greater the response in industry i to price shocks in industry j. ■

Differentiating equation (9) we obtain:

Corollary 2 *(a) The greater the efficiency of a conglomerate's operations in an industry, the greater the effect of price shocks in that industry on the optimal size of operations of the conglomerate in other industries. (b) The greater the efficiency of a conglomerate's operations in an industry, the smaller the effect diseconomies of scale in that industry on the transmission of shocks to the other industry.*

Proof

(a) We obtain part (a) is by differentiating equation (9) with respect to d_j. (b) Differentiating equation (18) with respect to d_j shows that the effect of returns of scale is smaller the greater the diseconomies of scale. ■

The corollary has several empirical implications. First, we would expect that shocks in a conglomerate's main segment (which, all else being equal, has a higher relative efficiency) would produce greater effects on the industries in which it has its peripheral segments than if the opposite were true. Second, the role of economies of scale differs in peripheral segments from that in main segments.

Note that we do not predict this pattern of sales and purchases because the conglomerate firms have an internal capital markets that are superior to those of single-industry firms. Rather, they result from the comparative advantage of conglomerates and single-segment firms over different ranges of demand.

II. Empirical Analysis: Firm Growth over the Business Cycle

We explore the previous predictions on how industry demand and supply conditions influence the growth of business segments. Our null hypothesis is that the growth is explained by industry demand and returns-to-scale, as well as firm-specific productivity, and that there are no agency costs.

To examine whether industry demand and supply conditions influence segment growth, we investigate both long-run changes in industry shipments and short-run changes in aggregate industry investment. By using detailed micro-level plant data, we can control for the changing composition of firms and accurately examine growth at the segment level.

We use three approaches to testing our model. First, we calculate the productivities of conglomerates (main and peripheral industry segments) and of single-segment firms, and examine whether they accord with the patterns predicted in Proposition 2. While this test has could reject our model, it does not allow us to differentiate between the model and agency models which posit that conglomerates invest in peripheral segments for noneconomic reasons.

To differentiate between our model and agency models, we examine and test the growth patterns of conglomerates and compare them to growth patterns of single-segment firms. One of our model's the key predictions is whether firms invest differently across business segments based on comparative advantage and returns to scale in business segments. Specifically, we test the prediction of Proposition 3 that conglomerates will grow less in a particular segment if their other segment(s) is (are) more productive and if their other segment(s) experiences a larger positive demand shock. Agency models do not predict this relation. Rather, they suggest that positive shocks in other segments provide additional resources for the expansion of peripherals.

Finally, as a robustness check, we identify a subsample of "failed" conglomerates that were split up over our sample period. If market forces are important in breaking up those conglomerates that have agency problems, then the failed conglomerates will be less likely to be follow optimal policies than will the complementary subsample of conglomerates that survive. Thus, by comparing the fit of our model in the two subsamples, we can check whether our regressions are detecting optimal resource allocation.

A. Data

We examine both multiple-segment conglomerate firms and single-segment firms by using an unbalanced panel for the period 1975 to 1992. To be in our sample, firms must have manufacturing operations producing products in SIC codes 2000-3999. We require firms to meet these criteria because of the unique nature of the micro-level data that we use to calculate plant-level productivity and industry-segment growth.

We use data from the Longitudinal Research Database (LRD), maintained by the Center for Economic Studies at the Bureau of the Census.[16] The LRD database contains detailed plant-level data on the value of shipments produced by each plant, investments broken down by equipment and buildings, and the number of employees.

There are several advantages to this database: First, it covers both public and private firms in manufacturing industries. Second, coverage is at the plant level, and output is assigned by plants at the four-digit SIC code level. Thus, firms that produce under multiple SIC codes are not assigned to just one industry. Third, plant-level coverage means that we can track plants even as they change owners.

The LRD tracks approximately 50,000 manufacturing plants every year in the Annual Survey of Manufactures (ASM). The ASM covers all plants with more than 250 employees. Smaller plants are randomly selected every fifth year to complete a rotating five-year panel.

We confine our analysis to 1975 through 1992. We use 1975 as the starting year of our analysis because it is the first year of a five-year panel; 1992 is the last year of data available to us. We aggregate our data into firm business-segment units at the three-digit SIC code from the individual plant-level data. We exclude segments that are less than $1 million in real value of shipments, and segments which have continuously compounded annual growth rates greater than 500% in absolute value.

We classify firms as single segment or multiple segment based on three-digit SIC codes. If a firm produces 97.5% of its sales or higher in one three-digit SIC code, we classify that firm as a single-segment firm and exclude the small peripheral segment. We classify all other firms are multiple-segment firms. For these firms, we also classify each segment as either a main segment or a peripheral segment. Main segments are segments whose real value of shipments (in 1982 dollars) is at least 25% of the firm's total shipments.

[16] For a more detailed description of the Longitudinal Research Database (LRD) see McGuckin and Pascoe (1988).

B. Variable Selection

In this section we describe the variables used to test our model and how we calculate the fundamental industry and segment-level variables used in our tests. Specifically, we use segment productivity, calculated industry returns-to-scale, business cycle indicators and the change in aggregate industry shipments to test the predictions of our propositions.

B1. Productivity of Business Segments

We calculate productivity for all firm segments at the plant level. Our primary measure of performance is total factor productivity (TFP). TFP takes the actual amount of output produced for a given amount of inputs and compares it to a predicted amount of output. "Predicted output" is what the plant should have produced, given the amount of inputs it used. A plant that produces more than the predicted amount of output has a greater-than-average productivity. This measure is more flexible than the cash flow measure, and does not impose the restrictions of constant returns to scale and constant elasticity of scale that a "dollar in, dollar out" cash flow measure requires.

In calculating the predicted output of each plant, we assume that for each industry there exists a production function that defines the relation between a plant's inputs and outputs. Then, for each industry we estimate this production function using an unbalanced panel with plant-level fixed effects, using all plants in the industry within our 1975 to 1992 time frame.

We assume that the plants in each industry have a translog production function. This functional form is a second-degree approximation to any arbitrary production function, and therefore takes into account interactions between inputs. To estimate predicted outputs, we take the translog production function and run a regression of log of the total value of shipments on the log of inputs, including cross-product and squared terms:

$$\ln Q_{it} = A + a_j \ln L_{jit} + \sum_{j=1}^{N} \sum_{k=j}^{N} a_{jk} \ln L_{jit} \ln L_{kit}, \tag{19}$$

where Q_{it} represents output of plant i in year t, and L_{jit} is the quantity of input j used in production for plant i for time period t. A is a technology shift parameter, assumed to be constant by industry, and $a_j = \sum_{i=1}^{N} a_{ji}$ indexes returns to scale.

Our measure of TFP is the residual from equation (19) plus the fixed effect. We standardize plant-level TFP by dividing by the standard deviation of TFP for each industry. Thus, our comparisons of plants' TFP are not driven by differences in the dispersion of productivity within each industry.

In estimating the TFPs in our sample, we use data for over 500,000 plant years, and for approximately 50,000 plants each year. In the productivity regression for each industry, we include three different types of inputs, capital, labor, and materials, as explanatory variables. All these data exist at the plant level. However, the ASM does not state the actual quantity shipped by each plant, but shows only the value of shipments. As a result, we take the difference between actual and predicted value of shipments as our measure of TFP. We adjust for inflation by using four-digit SIC code data from the Bartelsman and Gray (1994) database. We use data from the Bureau of Economic Analysis to make depreciation adjustments at the two-digit level. To capture vintage effects of capital, we include plant age in our productivity calculations. Plant age is the first year in which the plant appeared in the database, or 1972 (the first year of the database) whichever is earlier. Kovenock and Phillips (1997) describe these inputs and the method for accounting for inflation and depreciation of capital stock in more detail.

To measure the productivity for a firm's entire business segment, we construct a weighted average of individual plant productivity, in which the weights are the plant-level value of shipments. The variable for the productivity of the firm's other segments is the weighted average of all of the firm's other plants outside of the segment in question. Again, the weights are the plant-level value of shipments.

We also include other firm and segment-level variables in our regressions to provide additional control for unmeasured productivity differences and other factors, such as size, that can influence firm growth. We include the log of firm size and the number of plants operated by a firm at the beginning of the year. We define firm size as the total value of shipments.

B2. Industry Variables: Returns to Scale, Industry Shipments and Business-Cycle Classifications

We focus on shipment growth for two reasons. First, the value of capital and of allocating resources to growth in an industry depends on industry growth. Second, firms' cash constraints can depend on industry conditions. If firms in high-growth industries are less cash-constrained than those in declining industries, then firms might have different growth rates.

Similarly, industry returns-to-scale influence the value of allocating resources to a specific industry. We calculate several different measures of industry demand and supply conditions. Our central variables are industry-level return-to-scale, the yearly and long-run changes in industry shipments, and capacity utilization.

We calculate industry returns-to-scale, λ, by estimating a system of equations derived by assuming cost minimization for a given production function. The system consists of a translog production function and additional input demand equations. We estimate the translog production function simultaneously with input demand equations, equating input factor shares to the first-order conditions from the production function and imposing homogeneity of degree λ.

For industry shipments, we use the Bartelsman and Gray (1994) database at the three-digit SIC code level. We use industry shipments and investment data to investigate if long-run changes in an industry affect the relative growth of single-segment and conglomerate firms.

To determine whether the level of industry demand alters the relation between the explanatory variables and segment growth, we divide our sample of industries into quartiles according to level of demand. Where appropriate, we report results for both the entire sample and the quartiles.

We classify industries into "demand" or change-in-shipment quartiles by constructing an index of long-run changes in real industry shipments over a ten-year period. We include all industries in constructing these quartiles. We measure the change by using the log of a three-year average of total shipments during the years 1987 to 1989 divided by the three-year average from 1976 to 1978. We use the total value of shipments, a production-based number, for U.S. producers. Thus, this measure captures both cost shifts from increased foreign imports or shocks to production costs, and also demand changes in the industry. To avoid short-term changes in demand, we use three-year averages as the endpoints. We classify all the three-digit SIC industries in our database into quartiles that we base on our index of long-run changes in industry shipments. We use three-digit SIC industries to prevent smaller, four-digit industries from being overrepresented in any quartile. Then we examine the productivity of the segments of single-industry and multiple-segment firms by segment in these quartiles.

Note that by design, we do *not* have a similar number of conglomerate or single-segment firms in each quartile. If certain industries have more conglomerate firms, then the quartile containing these industries has more firms represented. Thus, we can examine whether declining industries have a higher frequency of conglomerates or single-segment firms, and whether the productivity of these firms is both significantly different from other firms in their quartile and from firms in other quartiles.

In addition to shipment-growth quartiles, we also classify industries into quartiles by annual changes in aggregate investment. We examine investments expressed in real 1982 dollars divided by total industry assets, also in real 1982 dollars. We use the Bartelsman and Gray (1994) data for investment and assets, and also their constructed price deflators. Classifying industries this way provides an aggregate industry-level measure of investment in an industry. These investment changes are proxies for the marginal productivity of capital and the expectation of future returns in the industry.

We then aggregate for each firms the plants it owns in each industry into industry segments, and examine the relative number and the productivity of industry segments of multiple- and single-segment firms in each quartile. To reduce sample selection problems, comparisons are across firms in that specific industry and quartile . Again, note that we do *not* have a similar number of firms in each quartile. Using this procedure, we examine whether multiple- and single-segment firms have differential growth rates just because they are in industries that experience different long-run growth rates.

Using aggregate industrial production data, we also classify years as recession or expansion years. We determine recession and expansion years by using aggregate and aggregate-detrended industrial production. We define detrended industrial production as the actual less predicted industrial production, where we calculate predicted industrial production from a regression of industrial production on a time trend. Recession years are years in which both real and detrended industrial production decline relative to the previous year. We classify years as expansion years when both real and detrended industrial production increase relative to the previous year.

This procedure gives us similar results as the NBER recession dating procedure, which NBER does quarterly. It also allows us to classify a year such as 1980, which, according to NBER, had a recession of less than six months. Using this procedure, we classify 1981-1982 and 1990-1991 as recession years and 1976-1978 and 1984-1988 as expansion years. Given that actual and detrended industrial production did not move in the same direction, 1979-1980, 1983, 1989, 1992 are indeterminate years

III. Results

A. Sample Summary Characteristics

Table I presents summary statistics for the firms in our dataset. We break out the statistics by single- and multiple-segment firms. We present both real-growth rates and the proportion of total real-dollar value of shipments by industry segments. We calculate real-growth rates by using individual plant-level shipments deflated by four-digit SIC code deflators from the NBER productivity database.

For multiple-segment firms, we subclassify their segments as either main or peripheral segments. We classify a segment as a main segment if it represents at least 25% of a firm's total value of shipments. (Note that a firm can have multiple "main" segments.) We also present real-growth rates by recession and expansion years for the segments that are in the top 50% of the distribution of total factor productivity. We determine recession and expansion years are determined as described in the previous section.

Insert Table I here

Table I shows that from 1980 to 1990, the proportion of output produced by single-segment firms in the U.S. manufacturing sector increased by five percentage points. This increase occurred because of a substantial increase in the number of new single-segment firms and because multiple-segment firms decreased production in their peripheral segments. We also see that multiple-segment firms' main divisions show almost a zero growth rate in recessions, and that single-segment firms and peripheral segments of multiple-segment firms register negative growth. Finally, the table shows that for both conglomerates and single-industry firms, efficient firms grow at substantially higher rates.

In Figure 1 we examine how the efficiency of conglomerates' segments varies with the size ranking of the segment within the conglomerate, and with the total number of segments. Figure 1 shows that there is a strong negative relation between the segment's rank and efficiency. This is consistent with the neo-classical hypothesis that conglomerates focus on the segment on which they have a comparative advantage. This within conglomerate drop-off in productivity in smaller segments suggests that managerial talent has an industry-specific component.

Insert Figure 1 here

Figure 1 also shows how the productivity of segments that are equally ranked by size within the conglomerate varies as the number of segments increases. Holding the within-conglomerate rank of a segment constant, its productivity increases as the total number of segments increases. Thus, for example, the mean efficiency of the largest segment of a two-segment conglomerate is lower than its industry average, whereas the mean efficiency of the largest segment of a conglomerate with more than ten segments or more is higher. This is consistent with the hypothesis that there are a number of large efficient conglomerates whose managerial talent is portable across industries. A larger number of conglomerates operate in a small number of segments, and are of less than average efficiency, even in their best industry. Again, this relation is consistent with the neo-classical model.

The comparison of equally-ranked segments for conglomerates of different sizes suggests that firms may become conglomerates for different reasons. Some firms may have above average managerial talent that is partially transferable across industries, and may exploit it optimally expanding into several industries. Other firms may have less than average managerial ability in their main industry, and may move into a second industry because they have attained their optimal size in their main segment. We would expect the former to be highly valued by the stock market and the latter to have a low valuation. As a result, it is difficult to interpret conglomerate discounts as evidence of agency problems. Instead, conglomerate discounts and premia may reflect the underlying distribution of managerial talent and the extent to which it is industry specific.

B. Growth and Efficiency over the Business Cycle

We first show how the average real growth and productivity of segments of single-segment and conglomerate firms can vary by size. Since our model predicts a different relation between productivity, size, and growth in response to positive and negative industry shocks, we report the results separately for expansion and recession years in the U.S. economy. These results appear in Tables II and III, respectively. In these tables, we define the size of each segment as the ratio of the size of the segment to the size of the median segment in the same industry, both measured at the beginning of the year.

Insert Table II here

Table II examines three predictions of our model. First, we test whether single-segment firms are more efficient than conglomerate firms. Second, we test whether the main divisions of conglomerate firms are more efficient than peripheral divisions. Third, we examine how the relation between growth and productivity during expansions and recessions differs for conglomerate firms' main and peripheral divisions.

Table II shows that single-segment firms have significantly higher productivity than conglomerate firms in four of the table's five size classes. The final column shows that conglomerate main divisions are significantly more productive than peripheral divisions for all size classes.

The third finding in Table II is that there is a strong positive association between growth and productivity in expansions, and that size is very important to this relation. Firms that are large at the beginning of the year tend to be more efficient, but grow at a slower rate than smaller firms. This finding seems to indicate that smaller firms grow much faster than large, efficient ones. However, small firms tend to have a wider range in efficiency. If we look at the most efficient 50% of firms for each size class, we find that growth rates do increase with efficiency. Finally, the table shows that conglomerates grow their efficient main divisions at a much faster rate than their inefficient peripheral divisions.

These results show that a relation exists between productivity and segment type, and that it is consistent with our model. As a result of this relation, the main and peripheral segments of conglomerates should not be investing similarly when there is a positive industry shock to demand. We explore this prediction in the regressions below.

Insert Table III here

Table III shows how recession affects the three segment types. First, for each size class, firm growth increases with efficiency for single-segment firms and for divisions of conglomerates. Second, conglomerate firms cut growth much more in their peripheral divisions than in their main divisions. Sales in their peripheral divisions decrease sharply, although for some size classes, the main divisions actually grow in real terms in the recession years. Finally, single-segment firms are more affected by recessions, but nevertheless show higher growth rates than do the peripheral divisions of the conglomerate firms.

We also explore the average annual growth rates for single-segment and multiple-segment firms during recession and expansion years for segments of different levels of efficiency. Our model predicts that the difference between the growth rates of efficient and inefficient firms should be lower during recessions than expansions. Thus, we compare the industry-adjusted annual growth rates of the most productive quartile of firm segments with the quartile of least productive segments. We find that the difference in annual growth rates between the most- and least-productive quartiles of industry segments was two to 2.5 percentage points higher in expansion years than in recession years.

Specifically, the difference in the growth rates between the main divisions of conglomerate firms in the highest productivity quartile and the main divisions in the lowest productivity quartile is two percentage points more during expansion years than during recession years.

For single-segment firms and peripheral segments, the difference in growth rates between segments in the highest and lowest productivity quartiles is 2.5 percentage points higher in expansions than in recessions.

Before we examine the regression results, we can draw three conclusions. First, during both expansions and recessions, growth increases with efficiency for nearly all size-based classifications in. Second, efficient firms grow relatively faster in expansion years than during recession years. This finding supports the prediction of our model that positive shocks effect efficient firms differently. Third, peripheral segments experience the worst real growth declines in recession years. This may imply that conglomerate firms either use their peripheral divisions to subsidize main divisions. Alternatively, conglomerates could be cutting back on inefficient divisions in response to large negative industry shocks, as predicted by the neoclassical model. We investigate these findings further in our regressions in the next section.

Table IV examines whether the disparity in the performance of conglomerate firms' main divisions and their peripheral divisions can be explained by industry differences. It could be that peripheral divisions are in low-growth industries and main divisions are in high-growth industries. To control for industry growth, Table IV presents results for the top and bottom quartiles of all industries based on the 12-year real-growth rate of shipments described in the earlier section.

Insert Table IV here

Table IV shows that separate long-run analyses of high- and low-growth industries does not substantively change the previous results. The sharp differences between the main and peripheral divisions of conglomerates remain. Peripheral divisions grow at a much slower rate and are less efficient both in high- and low-growth industries.

C. Growth and Relative Productivity with Industry Shocks

Table V examines the effect of productivity and industry fundamentals on the real-growth rates of conglomerate and single-segment firms in multivariate regressions. We measure the dependent variable, industry-adjusted segment growth, in real 1982 dollars, subtracting out the industry average for the entire period. Productivity and industry-segment size are also industry adjusted and represent deviations from industry averages.

To capture industry fundamentals we include both industry returns to scale (λ) and the annual change in real shipments. For each segment, we control for the segment's productivity

(TFP), the total the number of plants owned by the firm to which the segment belongs, and the log of firm size. The last two variables are lagged to represent values at the beginning of the year. Thus, for every segment, the regressions control for both the segment's own productivity, and for firm and industry characteristics.

Our model predicts that the growth of a segment depends on the interaction between the segment's productivity and the sign of the demand shock in the industry. For positive (negative) shocks, growth is positively (negatively) related to productivity. The magnitude of the effect depends on the returns-to-scale in the industry. To test for this interaction, we include a variable that interacts the change in industry demand with the segment's productivity.

Our model also predicts that the growth of a conglomerate firm's segment depends on the relative productivity demand conditions facing the firm's other segments. Specifically, a segment of a given productivity will grow faster (slower) if the firm's other, more-productive segments receive negative (positive) shocks and other, less-productive segments receive positive (negative) shocks. The magnitude of this effect also depends on the returns-to-scale in the other industries in which the conglomerate operates.

In our regressions, we use three variables to measure how the growth of a conglomerate firm's segment is affected by the firm's other segments. First, we measure the productivity of the other segments by weighing the TFP of each segment by its sales. Second, we test for the interaction between the segment's shock and the shocks in other segments by interacting the segment's relative industry demand with the other segments' weighted productivity. We measure relative industry demand by a variable that equals one (zero, minus one) when the segment's change in shipments at the industry level is greater (equal, less) than that of the firm's median segment. Our model predicts that this variable will have a negative coefficient. Third, to capture the returns-to-scale in the other segments, we also weigh the returns-to-scale in each of the industries in which the conglomerate operates by the sales in that industry. Our model predicts that firms grow less in a particular segment if other segments that are expanding have higher industry returns-to-scale.

We estimate the regression for all firms, both single- and multiple-segment firms, and for single- and multiple-segment firms separately. For the regression for all firms, the multiple-segment variables are equal to zero if the firm only has one industry segment. We estimate the regressions using unbalanced panel techniques and allowing for correlated residuals within panel units. Standard errors are corrected for heteroskedasticity.

Insert Table V here

The regression results in Table V show that industry returns-to-scale and the change in industry shipments are both highly significant and positively related to real firm growth. Multiple-segment firms are more sensitive to industry returns-to-scale and to the change in aggregate industry shipments than are single-segment firms. This suggests that conglomerates take into account the prospects of their other divisions. Both single- and multiple-segment firms' growth rates are significantly and positively related to segment productivity. The sensitivity is actually significantly greater for multiple-segment firms than it is for single-segment firms. This is in contrast to the prediction of agency models in which conglomerates dissipate resources. Firm size and the number of plants are both negatively related to firm growth, which suggests that there are additional decreasing returns to scale beyond those measured by the industry returns-to-scale parameter.

The evidence on the interaction effects is consistent with the predictions of our model. The own-segment interaction variable, real change in the segment's shipments times productivity, is positive and significant. Firms increase more in size when they receive a positive shock to a division in which they are efficient.

When we look at the interaction effects for conglomerate firms, we find evidence that the division's growth rate is affected by the prospects of the firm's other divisions. As predicted by our model, the segment's growth rate is negatively related to the interaction variable for a conglomerate's other divisions, relative demand times the other segments' productivity. Thus, segment growth is less when the other segments are more efficient and receive a positive demand shock. Finally, the negative coefficient on other segments' TFP shows that a segment grows at a lower rate when the other segments are more efficient.

These results show that firms grow faster in segments that are more efficient, and that they take into account the prospects of their other segments in a way that is consistent with the neoclassical maximizing firms in our model. While we do not have a precise benchmark for the optimal level of growth, the fact that conglomerate industry-adjusted growth rates are highly sensitive to segment productivity and to industry returns-to-scale is consistent with conglomerates making efficient resource allocation decisions.

D. Growth of Conglomerates' Main and Peripheral Divisions

Table VI estimates the same regressions, but breaks the conglomerate multiple-segment firms into their main and peripheral divisions. In the last column, we test for significant differences in coefficients between main and peripheral divisions of conglomerates.

Insert Table VI here

The results in Table VI show that main and peripheral divisions' growth rates have similar sensitivity to industry returns to scale and industry shipments. There are significant differences in the sensitivity of the segment growth to productivity. The peripheral segments are actually more sensitive to productivity. Conglomerate firms also grow their peripheral divisions less when they have other segments that are highly productive. Consistent with the neoclassical model, the interaction variable, relative demand times other segments' TFP, is significantly negative for both main and peripheral segments. These findings are consistent with efficient resource allocation to peripheral segments.

Overall, the results in Tables V and VI suggest that conglomerate firms take into account the prospects of other divisions when allocating resources that help the firm grow. We find that the growth rate of both main and peripheral segments responds positively to segment productivity and industry variables that capture the fundamental prospects for that division. Especially in peripheral segments, segment growth is dependent on productivity in both the division and the other divisions. These findings do not support the conclusion that conglomerate firms inefficiently allocate resources to peripheral divisions.

Table VII examines the economic significance of our regression results using the estimated coefficients from the regressions in Tables V and VI. We calculate predicted real-growth rates of conglomerate and single-segment firms as productivity and change in shipments varies from the 25th to the 75th percentiles. In computing these predicted growth rates, we hold all variables at their sample medians except productivity and change in industry shipments.

Insert Table VII here

The results in Table VII show that both single-segment and conglomerate firms are very sensitive to both productivity and the change in industry shipments. Comparing the results for single-segment firms and conglomerate firms' main divisions, we find that there is little economic difference in the predicted growth rates. There is an even smaller difference when we predict growth rates holding constant productivity across regressions. When we use productivity values for the median main segment of a conglomerate to estimate the predicted growth rate of single-segment firms, we obtain a predicted annual growth rate of 10.4% compared with 10.14% for a main segment of a conglomerate firm. This result confirms that most of the difference in observed growth rates between conglomerates and single-segment firms is driven by productivity differences.

Panel B of Table VII shows that both single-segment and conglomerate firms are highly sensitive to our measure of demand shocks, changes in industry shipments. Peripheral segments of conglomerate firms actually have predicted growth rates that are negative at the 25th percentile of change in shipments. This finding reinforces the earlier summary statistics, which show that in recessions conglomerate firms sharply cut the growth of unproductive peripheral divisions. There are substantial differences between predicted growth rates for main and peripheral segments, even when we use the data from the conglomerates' main divisions. This implies that differences in observed growth rates between main and peripheral segments are driven by differences in how the these segments grow when their productivities are equal, not just by productivity differences. The lower growth rates of peripheral divisions and the high sensitivity to productivity shows that conglomerate firms do not insulate their unproductive peripheral divisions from economic fundamentals.

E. Main and Peripheral Divisions in Recession Years

Table VIII examines the behavior of conglomerate firms' main and peripheral divisions in recession years. In the last column, we test for significant differences in coefficients between these divisions.

Insert Table VIII here

The results in Table VIII show that peripheral divisions' growth rates are sensitive to the productivity and fundamental industry factors. Especially interesting is the fact that the interaction of productivity with industry shipments is actually more significant for peripheral firms than it is for main divisions. Our findings reinforce the conclusion that there is no evidence that conglomerate firms insulate their peripheral divisions from recessions.

To examine further whether peripheral firms gain additional insulation from being part of conglomerate firms, we split peripheral segments into two groups based on the sensitivity of conglomerates' main divisions to recessions. Columns 1 and 2 present regressions for the peripheral divisions whose parents are in industries with greater than, and lower than, median sensitivity to recession, respectively.

Insert Table IX here

Table IX shows that there are similar effects for peripheral divisions no matter what the sensitivity of their parents' main division(s) may have to recession. Only two variables, lagged size and change in shipments interacted with productivity, differ significantly across parent types. The higher significance of the interaction variable, change in shipments times productivity, provides evidence that peripherals are better off with a parent company that is not exposed to the recession. However, none of the multiple-segment variables are significantly different.[17]

Insert Table X here

Table X examines the economic significance of our results. It shows that there is little economic difference between main and peripheral segments' responses to recessions. Thus, the observed differences in growth during recessions are attributable to differences in productivity of main and peripheral segments. However, when we classify peripherals by the exposure of their parents corporation's main segment(s) to the recession, then there is some evidence that when the parent's main segment(s) is more exposed to recession, peripherals shrink more. We then estimate the effect on growth for the peripheral division, using the productivity data from the conglomerate's main division. We find that the economic magnitude of the effect of having a more-exposed parent is economically much less important than is the difference between main and peripheral segments.

F. Robustness Tests

The preceding tables examine resource allocation, taking the organizational form of firms as given. We now identify conglomerates which become single-segment firms. We test whether the relation between growth and efficiency for this set of firms differs from that in surviving conglomerates.

F.1 Conglomerates which become Single-Segment Firms

[17] Note that the interaction variable, relative demand times TFP, has a different interpretation in this regression because we select the observations according to the magnitude of the shock in the main division(s).

Insert Table XI here

The results in Table XI show that the conglomerate firms that are broken up into single-segment firms do not respond as our model predicts to the multiple-segment variables. We note that there is an insignificant interaction of relative demand and other segments' weighted TFP for conglomerates that are broken up, but as our model predicts there is a negative, significant interaction for conglomerates which are not broken up. In addition, we find no effect for other segments' weighted TFP for the conglomerates that are broken up, but a negative, significant effect for the conglomerates that are not broken up. This evidence suggests that there is a subset of conglomerates that behave inefficiently, perhaps as a result of agency problems, and are therefore broken up.

Thus, we do find some evidence consistent with agency problems in conglomerate firms. However, even for these firms, we find no evidence that conglomerates significantly subsidize the growth of inefficient divisions. In addition, the signs of the coefficients of industry variables and productivity for the subsample of conglomerates that survive are consistent with optimal behavior. The results suggest that over our sample period, surviving conglomerates, which comprise the majority, grow efficiently across business segments.

F.2 Industry Cash Flow

Previous studies, most widely cited of which is Jensen (1986), identify cash flow as an important determinant of agency costs. Conglomerates can misallocate resources from industries in which they have high cash flows to segments in industries that do not have profitable investment opportunities. If such effects were important, we would expect a *positive* relation between segment growth rates and cash flow levels, and increases in other segments. Such a relation is empirically supported by Lamont (1997), who finds that when oil companies receive a favorable price shock, their peripheral divisions in other industries invest more than do their industry competitors. In contrast, in a neoclassical model there is no causal relation between other segments' cash flows and segment growth. However, to the extent that high cash flows in other segments signal future growth opportunities in those segments, our model would predict a *negative* relation between a segment's growth and other segments' cash flows when these are interacted with their relative productivity.[18] To test for the effect of cash flow on our sample's growth of segments, in Table XII we examine the effect of the level and

[18] Maksimovic and Phillips (1998) show that industry cash flow is a proxy for long-term growth opportunities.

change in a segment's cash flow on the growth of that and other segments. We control for the productivity of each segment and for other fundamental industry parameters.

Insert Table XII here

The results in Table XII show that firms do not grow industry segments faster when the other segments have higher cash flow. In fact, for the conglomerates that are not broken up, there is a negative significant effect of other segment's industry cash flow on segment growth. In particular, a segment grows more slowly when cash flows are high in other segments. This result is consistent with our model of optimal firm growth. For conglomerates that are broken up, we do not find evidence, either negative or positive, that other segments' industry cash flow influences segment growth.

An alternative indicator of how efficiently conglomerates allocate investment is how they respond to investment prospects across industries in which they operate. The usual measure of industry prospects is Tobin's q. Our model predicts that the sign will be negative when q is interacted with the other divisions' relative productivity. We proxy industry prospects using an industry Tobin's q constructed by weighting individual-firm qs. Paralleling our earlier results on industry change in shipments, we find a negative relation between a segment's growth and other segments' weighted Tobin's q interacted with segment efficiency.

However, we do not report these results, since there are two problems in using Tobin's q for our purposes. First, many industries do not have single-segment firms that match up to our three-digit SIC codes. In fact, approximately half of our sample did not match up. Second, our model predicts that single-segment firms have different valuations than conglomerates. Therefore, using single-segment Tobin's q cannot proxy for the prospects of conglomerates.

IV. Conclusions

Our paper explores how fundamental industry conditions and productivity influence segment growth for both single industry and multiple-segment conglomerate firms. We test hypotheses derived from a neoclassical model of firm activity in multiple markets with decreasing returns to scale from managerial ability. The model yields predictions about firm-size distributions of focused single-industry and multiple-segment firms as a function of firms' comparative advantage and industry demand shocks.

We find that conglomerate firms are less productive than are single-segment firms of a similar size. This difference is mainly driven by smaller peripheral divisions of the conglomerate, which show significantly lower productivity than do main segments. This evidence supports the hypothesis that firms invest in industries in which they have a comparative advantage. This is consistent with optimal resource allocation decisions by conglomerates *and* also with the conglomerate discount documented by Lang and Stulz (1994) and Berger and Ofek (1995). The evidence is consistent with conglomerates having a discount because of lower efficiency, not necessarily because of agency problems. Less-efficient firms can exist in equilibrium because of industry decreasing returns-to-scale.

Examining growth of firm segments, we find that the growth of productive and unproductive firm segments (both for single-segment firms and conglomerate firms) is consistent with the model of efficient growth across business segments. Segment growth is strongly related to fundamental industry factors and individual segment productivity. In particular, peripheral divisions' growth rates are highly sensitive to productivity. Conglomerate firms grow less in a particular segment if their other segment(s) is more productive and if their other segment(s) experiences a larger positive demand shock. Firms also grow less if their other industry exhibits higher returns-to-scale. In recessions, conglomerates tend to cut back on their less-productive peripheral segments. The differential pattern of efficiency and conglomerate growth across conglomerates' business segments, as well as a conglomerate discount, are consistent with a neoclassical model.

Our evidence is not consistent with conglomerates expanding inefficient divisions or protecting them from recessions by using resources from other divisions. Instead, peripheral segments are often marginal divisions whose growth declines when they have negative productivity. Our finding of high sensitivity of peripheral divisions to productivity is also consistent with the predictions of Stein (1997) in which conglomerates have an ability to allocate resources across divisions. These results hold both at the three-digit SIC code level reported in this paper and also at the two- and four-digit levels (not reported).

We do find some evidence that is consistent with some conglomerates having agency problems. We identify a subset of conglomerate firms whose growth decisions are, a priori, less likely to be consistent with our model of optimizing behavior. This subset comprises of conglomerates that were broken up during the 1980s. We find that the growth of these broken-up conglomerates is not consistent with our model of optimal growth. However, even for these firms, we find no evidence that conglomerates significantly subsidize the growth of inefficient divisions. The majority of conglomerate firms exhibit growth across business segments that is consistent with optimal behavior.

One major issue remains: We find that peripheral units of conglomerates are less productive than the main units, but that there is little evidence that peripheral growth is inefficient.

This pattern is consistent with our neoclassical model of firms' comparative advantage. However, this finding of negative relative productivity of conglomerates' peripheral divisions is also consistent with conglomerates having lower fixed costs of entry and lower costs of evaluating new ventures than do single-segment firms. In future research, we expect to identify in more detail how the growth, entry, and exit decisions of conglomerates' peripheral divisions differ from their industry competitors.

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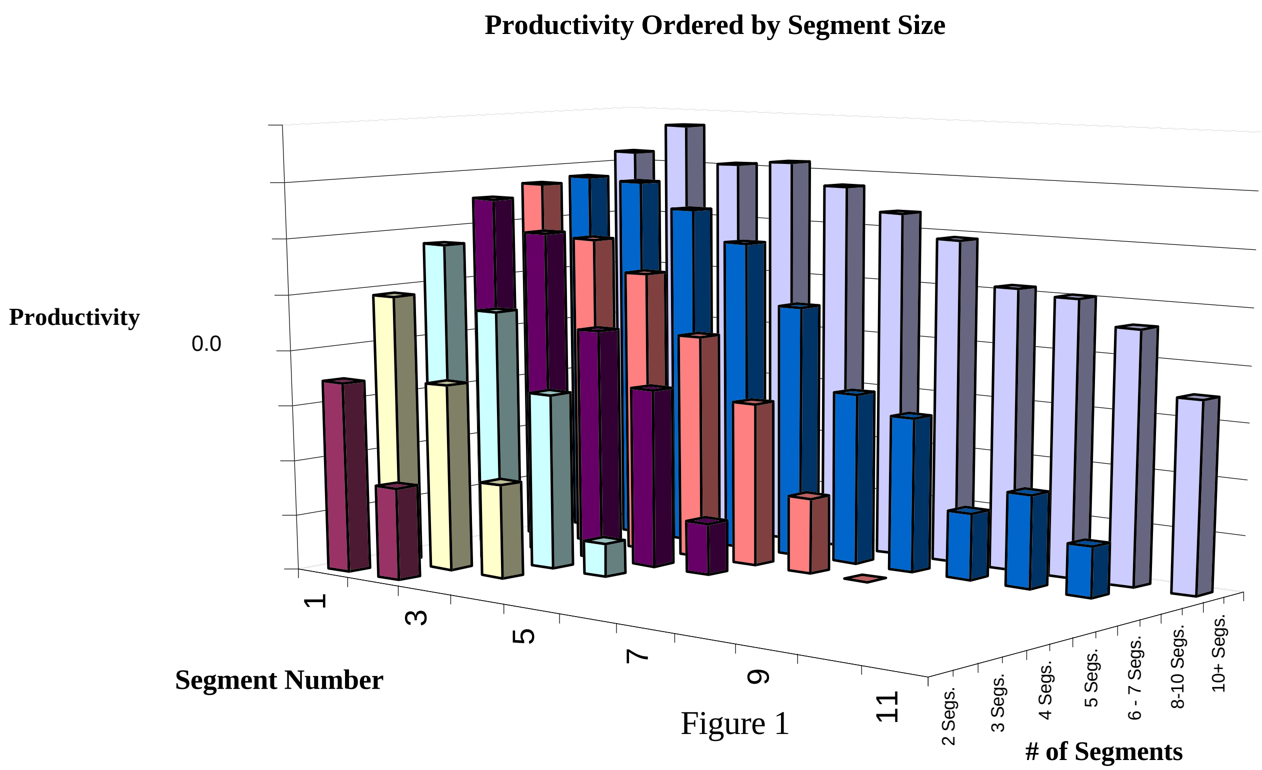
Productivity Ordered by Segment Size
Productivity
0.0
1
3
5
7
9
11
Segment Number
2 Segs.
3 Segs.
4 Segs.
5 Segs.
6 - 7 Segs.
8-10 Segs.
10+ Segs.
# of Segments

Figure 1

Table I
Sample Characteristics: Single-Segment and Multiple-Segment Firms

Sample characteristics of firms' industry operating segments. We calculate statistics from plant-level data aggregated into 3-digit SIC codes for each firm. We classify single-segment versus multiple-segment firms based on 3-digit SIC codes. For multiple-segment firms, main segments are segments that represent at least 25% of the firm's total shipments. We base size classifications on the previous year's real value of industry shipments relative to each industry's median value of shipments. We determine recession and expansion years using aggregate detrended industrial production. Recession years are years in which both real and detrended industrial production decline relative to the previous year. We classify years as expansion years when both real and detrended industrial production increase relative to the previous year.

	Sample of Firms		
	Single-Segment Firms	Multiple-Segment Firms	
Total Number of Firms			
Number of firms beginning of decade: 1980	13298	1929	
Number of firms end of decade: 1990	17321	2357	
Statistics by Industry Segments		Main Segments	Peripheral Segments
Number of segments - beginning of decade: 1980	13298	4880	2582
Number of segments - end of decade: 1990	17321	4745	3090
Proportion of Value of Shipments (All manufacturing industries)			
Beginning of decade: 1980	21.71%	50.75%	27.53%
End of decade: 1990	26.72%	49.65%	23.63%
Average Annual Industry Segment Growth Rate			
Recession years (1981-1982, 1990-1991)			
All industry segments	-5.15%	-0.01%	-5.48%
Firms' most productive segments [a] (top 50th percentile of TFP by industry)	-3.54%	1.57%	-4.06%
Expansion years (1976-1978, 1984-1988)			
All industry segments	2.46%	7.30%	2.60%
Firms' most productive segments [a] (top 50th percentile of TFP by industry)	5.99%	9.66%	4.35%

[a] Productivity is total factor productivity (TFP) and is a relative measure of productivity. TFPs are standardized by dividing each TFP by the standard deviation of the industry's TFP at the 3-digit level.

Table II
Growth and Productivity over the Business Cycle: Expansion Years

Sample characteristics of firms' industry operating segments in expansion years. We calculate statistics from plant-level data aggregated into 3-digit SIC codes for each firm. We classify single-segment versus multiple-segment firms based on 3-digit SIC codes. For multiple-segment firms, main segments are segments that represent at least 25% of the firm's total shipments. We base size classifications on the previous year's real value of industry shipments relative to each industry's median value of shipments. Number of segments is for the beginning of the period. We classify years as expansion years when both real and detrended industrial production increase relative to the previous year.

	Sample of Firms				
	Single-Segment Firms		Multiple-Segment Firms: Main Segments	Multiple-Segment Firms: Peripheral Segments	
Characteristics of firm operating segments in expansion years (average over 1976-1978, 1984-1988)					
Size Group 1: One-quarter to one-half of the industry median					
Average real growth of firm segment(s)	5.10%		9.44%	2.97%	
Growth of efficient segments (top 50% of TFP) [c]	13.70%		17.20%	11.40%	
Average productivity (TFP) of firm segment(s) [c]	-0.200		-0.121	-0.391	[b]
Number of firm segments	2025		213	65	
Size Group 2: One-half to 1 times the industry median					
Average real growth of firm segment(s)	3.44%		8.63%	1.86%	
Growth of efficient segments (top 50% of TFP) [c]	9.89%		13.80%	7.95%	
Average productivity (TFP) of firm segment(s) [c]	0.019	[a]	0.015	-0.298	[b]
Number of firm segments	1980		362	188	
Size Group 3: 1 to 2 times the industry median					
Average real growth of firm segment(s)	2.13%		9.08%	2.30%	
Growth of efficient segments (top 50% of TFP) [c]	7.27%		13.56%	7.32%	
Average productivity (TFP) of firm segment(s) [c]	0.197	[a]	0.120	-0.173	[b]
Number of firm segments	1195		412	274	
Size Group 4: 2 to 5 times the industry median					
Average real growth of firm segment(s)	1.43%		6.77%	3.19%	
Growth of efficient segments (top 50% of TFP) [c]	4.82%		9.30%	6.25%	
Average productivity (TFP) of firm segment(s) [c]	0.323	[a]	0.234	-0.077	[b]
Number of firm segments	576		547	560	
Size Group 5: greater than 5 times the industry median					
Average real growth of firm segment(s)	1.10%		6.15%	4.23%	
Growth of efficient segments (top 50% of TFP) [c]	2.67%		7.49%	6.70%	
Average productivity (TFP) of firm segment(s) [c]	0.422	[a]	0.375	0.154	[b]
Number of firm segments	171		731	3241	

[a] Significantly different from multiple segment firms at less than the 5% level using a 2-tailed test for the difference of the mean from 0.
[b] Significant difference between main and peripheral segments at less than the 5% level using a 2-tailed test for the difference of the mean from 0.
[c] Productivity is total factor productivity (TFP) and is a relative measure of productivity. TFPs are standardized by dividing each TFP by the standard deviation of the industry's TFP at the 3-digit level.

Table III
Growth and Productivity over the Business Cycle: Recession Years

Sample characteristics of firms' industry operating segments in recession years. We calculate statistics from plant-level data aggregated into 3-digit SIC codes for each firm. We classify single-segment versus multiple-segment firms based on 3-digit SIC codes. For multiple-segment firms, main segments are segments that represent at least 25% of the firm's total shipments. We base size classifications on the previous year's real value of industry shipments relative to each industry's median value of shipments. Number of segments is for the beginning of the period. We classify years as recession years when both real and detrended industrial production decrease relative to the previous year.

	Sample of Firms				
	Single-Segment Firms		Multiple-Segment Firms: Main Segments	Multiple-Segment Firms: Peripheral Segments	
Characteristics of firm operating segments in recession years (Average over 1981-1982, 1990-1991)					
Size Group 1: One-quarter to one-half of the industry median					
Average real growth of firm segment(s)	-1.50%		2.16%	-2.30%	
Growth of efficient segments (top 50% of TFP) [c]	7.57%		7.31%	4.79%	
Average productivity (TFP) of firm segment(s) [c]	-0.272		-0.169	-0.582	[b]
Number of firm segments	3380		116	31	
Size Group 2: One-half to 1 times the industry median					
Average real growth of firm segment(s)	-3.93%		0.64%	-6.44%	
Growth of efficient segments (top 50% of TFP) [c]	3.12%		6.49%	0.66%	
Average productivity (TFP) of firm segment(s) [c]	-0.037	[a]	-0.076	-0.481	[b]
Number of firm segments	3458		222	92	
Size Group 3: 1 to 2 times the industry median					
Average real growth of firm segment(s)	-5.10%		-0.75%	-8.10%	
Growth of efficient segments (top 50% of TFP) [c]	-0.03%		4.77%	-3.11%	
Average productivity (TFP) of firm segment(s) [c]	0.173	[a]	0.061	-0.198	[b]
Number of firm segments	2495		341	130	
Size Group 4: 2 to 5 times the industry median					
Average real growth of firm segment(s)	-5.50%		-1.07%	-5.35%	
Growth of efficient segments (top 50% of TFP) [c]	-1.90%		1.52%	-0.36%	
Average productivity (TFP) of firm segment(s) [c]	0.314	[a]	0.188	-0.131	[b]
Number of firm segments	1616		630	390	
Size Group 5: greater than 5 times the industry median					
Average real growth of firm segment(s)	-6.20%		-0.84%	-4.20%	
Growth of efficient segments (top 50% of TFP) [c]	-3.16%		0.60%	-0.78%	
Average productivity (TFP) of firm segment(s) [c]	0.379	[a]	0.373	0.175	[b]
Number of firm segments	1226		1305	3967	

[a] Significantly different from multiple segment firms at less than the 5% level using a 2-tailed test for the difference of the mean from 0.

[b] Significant difference between main and peripheral segments at less than the 5% level using a 2-tailed test for the difference of the mean from 0.

[c] Productivity is total factor productivity (TFP) and is a relative measure of productivity. TFPs are standardized by dividing each TFP by the standard deviation of the industry's TFP at the 3-digit level.

Table IV
Sample Characteristics: Growth and Productivity for Low- and High-Growth Industries

Sample characteristics of firms' industry operating segments for high- and low-growth industries. A industry is classified as high (low) growth when it is in the top (bottom) quartile of industry real growth over a 12-year period with endpoints given by the averag over three years, 1976-1978 and 1987-1989. We calculate statistics from plant-level data aggregated into 3-digit SIC codes for each firm's segments. For multiple-segment firms, main segments are segments that represent at least 25% of the firm's total shipments.

	Sample of Firms		
	Single-Segment	Multiple-Segment Firms	
	Firms	Main Segments	Peripherial Segments
Panel A: Characteristics of Firm Operating Segments in Expansion Years for Low-Growth Industries			
Size Group 1: One-quarter to one-half of the industry median			
Average real growth of firm segment(s)	2.96%	8.31%	***
Growth of efficient segments (top 50% of TFP[a])	11.25%	16.89%	
Average productivity (TFP) of firm segment(s)[a]	-0.11	-0.06	
Number of firm segments	281	29	
Size Group 2: One-half to 1 times the industry median			
Average real growth of firm segment(s)	1.17%	6.21%	2.55%
Growth of efficient segments (top 50% of TFP[a])	6.74%	9.68%	7.31%
Average productivity (TFP) of firm segment(s)[a]	0.05	0.01	-0.08
Number of firm segments	266	63	27
Size Group 3: 1 to 2 times the industry median			
Average real growth of firm segment(s)	-1.03%	8.21%	0.35%
Growth of efficient segments (top 50% of TFP[a])	4.68%	10.63%	6.27%
Average productivity (TFP) of firm segment(s)[a]	0.10	0.05	-0.09
Number of firm segments	164	77	31
Size Group 4: 2 to 5 times the industry median			
Average real growth of firm segment(s)	0.08%	5.79%	0.10%
Growth of efficient segments (top 50% of TFP[a])	3.95%	9.33%	3.26%
Average productivity (TFP) of firm segment(s)[a]	0.19	0.12	-0.04
Number of firm segments	86	84	66
Size Group 5: greater than 5 times the industry median			
Average real growth of firm segment(s)	-0.01%	2.28%	0.27%
Growth of efficient segments (top 50% of TFP[a])	0.60%	3.67%	3.27%
Average productivity (TFP) of firm segment(s)[a]	0.14	0.22	0.11
Number of firm segments	17	104	340

*** Cell cannot be disclosed because of limited number of observations.

[a] Productivity is total factor productivity (TFP) and is a relative measure of productivity. TFPs are standardized by dividing each TFP by the standard deviation of the industry's TFP at the 3-digit level.

Table IV (continued)
Sample Characteristics: Growth and Productivity for High-Growth Industries

Panel B: Characteristics of Firm Operating Segments in Expansion Years for High-Growth Industries

Size Group 1: One-quarter to one-half of the industry median			
Average real growth of firm segment(s)	6.19%	12.61%	-1.82%
Growth of efficient segments (top 50% of TFP) [a]	15.41%	22.93%	19.04%
Average productivity (TFP) of firm segment(s) [a]	-0.24	-0.10	-0.51
Number of firm segments	419	63	23
Size Group 2: One-half to 1 times the industry median			
Average real growth of firm segment(s)	4.68%	11.48%	-0.01%
Growth of efficient segments (top 50% of TFP) [a]	10.44%	17.96%	9.18%
Average productivity (TFP) of firm segment(s) [a]	0.01	0.05	-0.34
Number of firm segments	370	104	71
Size Group 3: 1 to 2 times the industry median			
Average real growth of firm segment(s)	3.93%	11.20%	0.93%
Growth of efficient segments (top 50% of TFP) [a]	9.15%	16.39%	9.33%
Average productivity (TFP) of firm segment(s) [a]	0.19	0.11	-0.23
Number of firm segments	195	85	87
Size Group 4: 2 to 5 times the industry median			
Average real growth of firm segment(s)	2.54%	8.35%	3.09%
Growth of efficient segments (top 50% of TFP) [a]	6.44%	10.52%	10.21%
Average productivity (TFP) of firm segment(s) [a]	0.38	0.28	-0.16
Number of firm segments	94	134	173
Size Group 5: greater than 5 times the industry median			
Average real growth of firm segment(s)	2.96%	8.23%	5.77%
Growth of efficient segments (top 50% of TFP) [a]	4.67%	10.15%	10.65%
Average productivity (TFP) of firm segment(s) [a]	0.53	0.43	0.14
Number of firm segments	22	174	884

*** Cell cannot be disclosed because of limited number of observations.

[a] Productivity is total factor productivity (TFP) and is a relative measure of productivity. TFPs are standardized by dividing each TFP by the standard deviation of the industry's TFP at the 3-digit level.

Table V
Firm Industry Segment Growth

Regressions test the effects of plant-level productivity and industry-level demand on firm industry segment sales growth for single- and multiple-segment firms. The dependent variable, firm segment growth, is growth less the industry average for the entire period. Segment size and productivity are industry-adjusted in each year. Data are aggregated into firm 3-digit SIC codes for industry segments from underlying plant-level data. We estimate the regressions using unbalanced panel regressions allowing for correlated residuals within panel units. Significance tests are conducted using heteroskedasticity-consistent standard errors following Huber-White. Data are yearly from 1975 to 1992. (p-values are in parentheses.)

	Dependent Variable: Firm Industry Segment Growth			**Test for Significant Diff.:**
Variable	All Firm Industry Segments	Single-Segment Firms	Multiple-Segment Firms	**Multiple-Segment Interaction Variable (p-value)** [h]
Constant	-0.052	0.039	-0.123	
	(.000) [a]	(.002) [a]	(.000) [a]	(.000) [a]
Industry returns to scale (λ) [d]	0.092	0.036	0.194	
	(.000) [a]	(.010) [a]	(.000) [a]	(.000) [a]
Change in aggregate industry shipments	0.688	0.627	0.805	
	(.000) [a]	(.000) [a]	(.000)	(.000) [a]
Firm segment productivity (TFP) [e]	0.079	0.081	0.084	
	(.000) [a]	(.000) [a]	(.000) [a]	(.013) [b]
Change in shipments*TFP	0.041	0.051	0.009	
	(.002) [a]	(.001) [a]	(.717)	(.115)
ln(lagged firm segment size)	-0.002	0.172	-0.004	
(coefficient*10,000,000)	(.264)	(.000) [a]	(.032) [b]	(.000) [a]
Number of plants owned by firm	-0.314	-23.290	-0.279	
(beginning of year, coeff*1,000)	(.000) [a]	(.000) [a]	(.000) [a]	(.000) [a]
Firm multiple-segment variables				
Other segment's weighted TFP [f]	-0.007		-0.008	
	(.002) [a]		(.000) [a]	
Relative demand * other segments	-0.006		-0.008	
weighted TFP [g]	(.006) [a]		(.001) [a]	
Other segment's weighted	-0.023		-0.051	
returns to scale (λ) [f]	(.000) [a]		(.000) [a]	
Total industry-segment years	400,046	251,927	148,119	
Chi - squared statistic	12257.56	8977.01	4396.03	
Significance level (p-value)	<1%	<1%	<1%	

a, b, c : Significantly different from 0 at the 1%, 5%, and 10% levels, respectively, using a 2-tailed test.

[d] Returns to scale, λ, is calculated at the 3-digit industry segment level by imposing homogeneity of degree λ to input demand equations when estimating a translog production function.

[e] Total Factor Productivity (TFP) is calculated using a translog production function.

[f] Other segments' productivity (and returns to scale) are weighted averages of the firm's other segment(s) weighted by the segment(s) sales.

[g] Relative industry demand is interacted with other segments' productivity and equals 1 (0, -1) when the segment's change in shipments at the industry level is greater (equal, less) than that of the firm's median segment.

[h] Signficance test for a multiple-segment dummy variable interacted with each independent variable in a regression with all firm segments.

Table VI
Conglomerate Industry Segment Growth

Regressions test the effects of plant-level productivity and industry-level demand on firm industry segment sales growth for main divisions (greater than 25% of firm sales) and peripheral segments of multiple-segment firms. The dependent variable, firm segment growth, is growth less the industry average for the entire period. Segment size and productivity are industry-adjusted in each year. We estimate the regressions using unbalanced panel regressions allowing for correlated residuals within panel units. Significance tests are conduced using heteroskedasticity-consistent standard errors following Huber-White. Data are aggregated into firm three digit industry segments from underlying plant-level data with yearly observations from 1975 to 1992. (p-values are in parentheses.)

	Dependent Variable: Firm Industry Segment Growth		**Test for Significant Diff.**
	Multiple Segment Firms		**Main - Peripheral Segment**
Variable	Main Segment(s)	Peripheral Segment(s)	**Firms (p-value)**
Constant	-0.077	-0.274	
	(.035) [b]	(.000) [a]	(.075) [c]
Industry returns to scale (λ) [d]	0.166	0.151	
	(.000) [a]	(.000) [a]	(.963)
Change in aggregate industry shipments	0.840	0.817	
	(.000) [a]	(.000) [a]	(.624)
Firm segment productivity (TFP) [e]	0.064	0.095	
	(.000) [a]	(.000) [a]	(.000) [a]
Change in shipments*TFP	-0.070	0.042	
	(.095) [c]	(.189)	(.032) [b]
ln(lagged firm segment size)	-0.015	-0.005	
(coefficient*10,000,000)	(.197)	(.026) [b]	(.405)
Number of plants owned by firm	-0.587	0.001	
(beginning of year, coeff*1,000)	(.000) [a]	(.974)	(.000) [a]
Firm multiple-segment variables			
Other segment's weighted TFP [f]	0.003	-0.002	
	(.349)	(.600)	(.190)
Relative demand * other segments	-0.005	-0.014	
weighted TFP [g]	(.060) [c]	(.001) [a]	(.059) [c]
Other segment's weighted	-0.031	0.122	
returns to scale (λ) [f]	(.003) [a]	(.103)	(.001) [a]
Total industry-segment years	56,132	91,987	
Chi - squared statistic	1701.25	2758.86	
Significance level (p-value)	<1%	<1%	

a, b, c : Significantly different from 0 at the 1%, 5%, and 10% levels, respectively, using a 2-tailed test.

[d] Returns to scale, λ, is calculated at the 3-digit industry segment level by imposing homogeneity of degree λ to input demand equations when estimating a translog production function.

[e] Total Factor Productivity (TFP) is calculated using a translog production function.

[f] Other segments' productivity (and returns to scale) are weighted averages of the firm's other segment(s) weighted by the segment(s) sales.

[g] Relative industry demand is interacted with other segments' productivity and equals 1 (0, -1) when the segment's change in shipments at the industry level is greater (equal, less) than that of the firm's median segment.

[h] Signficance test for a multiple-segment dummy variable interacted with each independent variable in a regression with all firm segments.

Table VII
Economic Significance of Regression Results

Predicted real growth rates of multiple- and single-segment firms as productivity and change in shipments varies from the 25th to the 75th percentiles. We compute these predicted growth rates holding all variables except productivity and change in industry shipments at their sample medians.
We calculate predicted real annual growth rates using coefficient estimates from Table 5 & 6.

Predicted Real Annual Growth Rates at the:	25th Percentile	50th Percentile	75th Percentile
Varying Total Factor Productivity:			
Single-segment firms (own productivity data):	0.36%	4.55%	8.59%
Productivity data from conglomerates' main segments	3.20%	6.66%	10.40%
(Both use coefficients from Table 5, column 2)			
Multiple-segment conglomerate firms:			
All segments	-0.69%	3.18%	7.00%
(using coefficients from Table 5, column 3)			
Main segments	4.65%	7.32%	10.14%
(using coefficients from Table 6, column 1)			
Peripheral segments (own productivity data)	-4.26%	-0.29%	4.81%
Productivity data from conglomerates' main segments	-3.06%	0.98%	5.34%
(Both use coefficients from Table 6, column 2)			
Varying Change in Industry Shipments:			
Single-segment firms (own data):	1.87%	4.55%	7.08%
Data from conglomerates' main segments	4.02%	6.93%	9.63%
(Both use coefficients from Table 5, column 2)			
Multiple-segment conglomerate firms:			
All segments (own data)	-0.72%	3.11%	6.84%
(Using coefficients from Table 5, column 3)			
Main segments	3.50%	7.32%	10.80%
(using coefficients from Table 6, column 1)			
Peripheral segments	-3.66%	0.29%	4.26%
Shipments data from conglomerates' main segments	-3.51%	0.26%	3.75%
(Both use coefficients from Table 6, column 2)			

Table VIII
Conglomerate Industry Segment Growth in Recession Years

Regressions test the effects of plant-level productivity and industry-level demand on firm industry segment sales growth for main divisions and peripheral segments of multiple segment firms in recessions. Recession years are 1981, 1982, 1990, and 1991, identified using detrended and aggregate industrial production. The dependent variable, firm-segment growth, is growth less the industry average for the entire period. Segment size and productivity are industry adjusted in each year. Data are aggregated into firm 3-digit industry segments from underlying plant-level data. We estimate the regressions using unbalanced panel regressions allowing for correlated residuals within panel units. Significance tests are conduced using heteroskedasticity-consistent standard errors following Huber-White. Data are yearly from 1975 to 1992. (p-values are in parentheses.)

Dependent Variable: Firm Industry Segment Growth in Recession Years			**Test for Significant Diff.**
	Multiple-Segment Firms		**Main - Peripheral Segment [h]**
Variable	Main Segment(s)	Peripheral Segment(s)	**Firms (p-value)**
Constant	-0.046	-0.187	
	(.514)	(.218)	(.152)
Industry returns to scale (λ) [d]	0.129	0.180	
	(.079) [c]	(.046) [b]	(.671)
Change in aggregate industry shipments	0.624	0.697	
	(.000) [a]	(.000) [a]	(.307)
Firm segment productivity (TFP) [e]	0.051	0.088	
	(.000) [a]	(.000) [a]	(.000) [a]
Change in shipments*TFP	-0.139	0.167	
	(.133)	(.024) [b]	(.010) [a]
ln(lagged firm segment size)	-0.031	-0.011	
(coefficient*10,000,000)	(.098) [c]	(.001) [a]	(.321)
Number of plants owned by firm	-0.081	0.272	
(beginning of year, coeff*1,000)	(.696)	(.018) [b]	(.139)
Firm multiple-segment variables			
Other segment's weighted TFP [f]	-0.002	-0.018	
	(.706)	(.050) [b]	(.147)
Relative demand * other segments	-0.003	-0.012	
weighted TFP [g]	(.633)	(.167)	(.367)
Other segment's weighted	-0.059	-0.021	
Returns to Scale (λ) [f]	(.018) [b]	(.889)	(.018) [b]
Total industry-segment years	12,337	18,667	
Chi - squared statistic	259.86	432.65	
Significance level (p-value)	<1%	<1%	

a, b, c : Significantly different from 0 at the 1%, 5%, and 10% levels, respectively, using a 2-tailed test.

[d] Returns to scale, λ, is calculated at the 3-digit industry segment level by imposing homogeneity of degree λ to input demand equations when estimating a translog production function.

[e] Total Factor Productivity (TFP) is calculated using a translog production function.

[f] Other segments' productivity (and returns to scale) are weighted averages of the firm's other segment(s) weighted by the segment(s) sales.

[g] Relative industry demand is interacted with other segments' productivity and equals 1 (0, -1) when the segment's change in shipments at the industry level is greater (equal, less) than that of the firm's median segment.

[h] Signficance test for a main-segment dummy variable interacted with each independent variable in a regression with all firm segments.

Table IX
Peripheral Division Growth in Recession Years

Regressions test the effects of plant-level productivity and industry-level demand on firm peripheral segment sales growth. Regressions are estimated for peripheral divisions based on the conglomerates main divisions' sensitivity to recessions. High- (low-) sensitivity main divisions are conglomerates whose main division's industry experiences a change in industry industry shipments greater (less) than the 50th percentile in recession years 1981, 1982, 1990, and 1991. The dependent variable, firm-segment growth, is growth less the industry average for the entire period. Segment size and productivity are industry-adjusted in each year. Data are aggregated into firm 3-digit industry segments from underlying plant-level data. We estimate the regressions using unbalanced panel regressions allowing for correlated residuals within panel units. Significance tests are conduced using heteroskedasticity-consistent standard errors following Huber-White. Data are yearly from 1975 to 1992. (p-values are in parentheses.)

Dependent Variable: Peripheral Division Growth in Recession Years			
	Peripheral Segments		Test for Significant I
	Main Segment(s) Sensitivity to Recession		Low - High Sensitivi
Variable	Low Sensitivity	High Sensitivity	**Firms (p-value)**
Constant	-0.204	-0.234	
	(.262)	(.393)	(.709)
Industry returns to scale (λ) [d]	0.129	0.248	
	(.331)	(.042) [b]	(.504)
Change in aggregate industry	0.754	0.670	
shipments	(.000) [a]	(.000) [a]	(.513)
Firm segment productivity (TFP) [e]	0.095	0.081	
	(.000) [a]	(.000) [a]	(.262)
Change in shipments*TFP	0.322	0.047	
	(.011) [b]	(.589)	(.077) [c]
ln(lagged firm segment size)	-0.045	-0.008	
(coefficient*10,000,000)	(.012) [b]	(.021) [b]	(.048) [b]
Number of plants owned by firm	0.744	0.121	
(beginning of year, coeff*1,000)	(.007) [a]	(.382)	(.057) [c]
Firm multiple-segment variables			
Other segment's weighted TFP [f]	-0.029	-0.005	
	(.033) [b]	(.684)	(.201)
Relative demand * other segments	-0.016	-0.013	
weighted TFP [g]	(.214)	(.272)	(.925)
Other segment's weighted	0.047	-0.041	
returns to scale (λ) [f]	(.764)	(.891)	(.818)
Total industry-segment years	9,641	9,026	
Chi - squared statistic	235.92	208.77	
Significance level (p-value)	<1%	<1%	

a, b, c : Significantly different from 0 at the 1%, 5%, and 10% levels, respectively, using a 2-tailed test.

[d] Returns to scale, λ, is calculated at the 3-digit industry segment level by imposing homogeneity of degree λ to input demand equations when estimating a translog production function.

[e] Total Factor Productivity (TFP) is calculated using a translog production function.

[f] Other segments' productivity (and returns to scale) are weighted averages of the firm's other segment(s) weighted by the segment(s) sales.

[g] Relative industry demand is interacted with other segments' productivity and equals 1 (0, -1) when the segment's change in shipments at the industry level is greater (equal, less) than that of the firm's median segment.

[h] Signficance test for a high-sensitivity dummy variable interacted with each independent variable in a regression with all firm segments.

Table X
Economic Significance in Recessions

Predicted real growth rates of conglomerate and single-segment firms as productivity and change in shipments varies from the 25th to the 75th percentiles. We compute these predicted growth rates holding all variables except productivity and change in industry shipments at their sample medians.
We calculate predicted annual real growth rates using coefficient estimates from Table VIII & IX.

Predicted Real Annual Growth Rates at the:	25th Percentile	50th Percentile	75th Percentile
Varying Total Factor Productivity:			
Multiple-segment conglomerate firms:			
Main segments	-0.27%	1.97%	4.55%
(using coefficients from Table 8, column 1)			
Peripheral segments (own productivity data)	-8.37%	-4.17%	-0.01%
(using coefficients from Table 8, column 2)			
Peripheral segments (productivity data from main segments)	-7.49%	-3.78%	0.30%
Peripheral segments with:			
Parent main division less sensitive to recessions	-7.79%	-3.19%	1.40%
(using coefficients from Table 9, column 1)			
Parent main division more sensitive to recessions	-8.79%	-4.90%	-1.13%
(using coefficients from Table 9, column 2)			
Varying Change in Industry Shipments:			
Multiple-segment conglomerate firms:			
Main segments	-0.47%	1.97%	4.05%
(using coefficients from Table 8, column 1)			
Peripheral segments (own shipments data)	-7.07%	-4.17%	-0.01%
(using coefficients from Table 8, column 2)			
Peripheral segments (shipments data from main segments)	-6.88%	-3.88%	-1.43%
Peripheral segments with:			
Parent main division less sensitive to recessions	-5.90%	-3.19%	-0.40%
(using coefficients from Table 9, column 1)			
Parent main division more sensitive to recessions	-7.61%	-4.90%	-2.21%
(using coefficients from Table 9, column 2)			

Table XI
Conglomerate Firms that Become Single-Segment Firms

Regressions test the effects of firm and industry-level variables on segment sales growth for conglomerate firms that become single industry segment firms. The dependent variable, firm segment growth, is growth less the industry average for the entire period. Segment size and productivity are industry adjusted in each year. We estimate the regressions using unbalanced panel regressions, allowing for correlated residuals within panel units. Significance tests are conduced using heteroskedasticity-consistent standard errors following Huber-White. Data are aggregated into firm 3-digit industry segments from underlying plant-level data with yearly observations from 1975 to 1992. (p-values are in parentheses.)

Dependent Variable: Firm Industry Segment Growth				
	Conglomerate Firms that Become Single Segment Firms			**Test for Significant Diff. Column 1 - Column 3**
	Conglomerate Period	Single Segment Period	Firms that remain Conglomerates	**(p-value) [h]**
Constant	-.286	-.183	-.184	
	(.000) [a]	(.001) [a]	(.000) [a]	(.000) [a]
Industry returns to scale (λ) [d]	.137	.274	.207	
	(.014) [b]	(.000) [a]	(.000) [a]	(.247)
Change in aggregate industry shipments	.807	.812	.815	
	(.000) [a]	(.000) [a]	(.000) [a]	(.773)
Firm segment productivity (TFP) [e]	.096	.090	.080	
	(.000) [a]	(.000) [a]	(.000) [a]	(.011) [b]
Change in shipments*TFP	-.048	.057	.010	
	(.418)	(.417)	(.729)	(.325)
ln(lagged firm segment size)	-.028	.163	-.004	
(coefficient*10,000,000)	(.540)	(.018) [b]	(.043) [b]	(.583)
Number of plants owned by firm	-.515	-23.717	-.251	
(beginning of year, coeff*1,000)	(.040) [b]	(.000) [a]	(.000) [a]	(.319)
Firm multiple-segment variables				
Other segment's weighted TFP [f]	.000		-.014	
	(.987)		(.000) [a]	(.004) [a]
Relative demand * other segments weighted TFP [g]	.000		-.012	
	(.987)		(.000) [a]	(.021) [b]
Other segment's weighted returns to scale (λ) [f]	.166		.001	
	(.009) [a]		(.973)	(.026) [b]
Total industry-segment years	23,778	19,944	105,390	
Total number of firms	1,228		1,747	
Chi - squared statistic	941.95	570.41	3082.18	
Significance level (p-value)	<1%	<1%	<1%	

a, b, c : Significantly different from 0 at the 1%, 5%, and 10% levels, respectively, using a 2-tailed test.

[d] Returns to scale, λ, is calculated at the 3-digit industry segment level by imposing homogeneity of degree λ to input demand equations when estimating a translog production function.

[e] Total Factor Productivity (TFP) is calculated using a translog production function.

[f] Other segments' productivity (and returns to scale) are weighted averages of the firm's other segment(s) weighted by the segment(s) sales.

[g] Relative industry demand is interacted with other segments' productivity and equals 1 (0, -1) when the segment's change in shipments at the industry level is greater (equal, less) than that of the firm's median segment.

[h] Signficance test for a dummy variable for conglomerates that are broken up interacted with each independent variable including all firm segments.

Table XII
Robustness Tests: Including Industry Cash Flow

Regressions include industry-level cashflow to test the robustness of prior results to alternative measures of the potential for inefficient resource allocation. We include both industry cashflow for the segment in question and for the firm's other segments. We interact the industry cash flow of the other firm's segment(s) with the weighted productivity of these segments.
As before, the dependent variable, firm-segment growth, is growth less the industry average for the entire period.
Data are aggregated into firm 3-digit industry segments from underlying plant-level data.
We estimate the regressions using unbalanced panel regressions, allowing for correlated residuals within panel units.
Significance tests are conduced using heteroskedasticity-consistent standard errors following Huber-White. Data are yearly from 1975 to 1992. (p-values are in parentheses.)

	Dependent Variable: Firm Industry Segment Growth			
	Conglomerate Firms that Become Single-Segment Firms			**Test for Significant Diff. Column 1 - Column 3**
	Conglomerate Period	Single-Segment Period	Firms that remain Conglomerates	**(p-value)**
Constant	-.300	-.191	-.056	
	(.001)[a]	(.006)[a]	(.219)	(.013)[a]
Industry returns to scale (λ)[d]	.128	.281	.208	
	(.036)	(.000)[a]	(.000)[a]	(.231)
Industry cash flow (weighed by industry sales.)	-.011	.005	-.001	
	(.721)	(.865)	(.953)	(.791)
Change in aggregate industry shipments	.806	.812	.817	
	(.000)[a]	(.000)[a]	(.000)[a]	(.716)
Firm segment productivity (TFP)[e]	.096	.090	.081	
	(.000)[a]	(.000)[a]	(.000)[a]	(.014)[b]
Change in shipments*TFP	-.048	.057	.011	
	(.418)	(.417)	(.702)	(.318)
ln(lagged firm segment size)	-.025	.164	-.005	
(coefficient*10,000,000)	(.585)	(.018)[b]	(.016)[b]	(.643)
Number of plants owned by firm	-.516	-23.705	-.273	
(beginning of year, coeff*1,000)	(.040)[b]	(.000)[a]	(.000)[a]	(.364)
Firm multiple-segment variables				
Other segment's weighted TFP[e]	-.006		.004	
	(.787)		(.740)	(.713)
Relative demand * other segments	.000		-.012	
weighted TFP[f]	(.977)		(.000)[a]	(.022)[b]
Other segment's weighted	.185		-.097	
returns to scale (λ)[g]	(.009)[a]		(.013)[b]	(.001)[a]
Other segment's weighted	.021		-.082	
industry cash flow	(.566)		(.000)[a]	(.010)[a]
Industry cash flow* other segments	.013		-.037	
weighted TFP	(.783)		(.194)	(.368)
Total industry-segment years	23,778	19,944	105,390	
Total number of firms	1,228		1,747	
Chi - squared statistic	943.72	570.77	3136.79	
Significance level (p-value)	<1%	<1%	<1%	

a, b, c : Significantly different from 0 at the 1%, 5%, and 10% levels, respectively, using a 2-tailed test.

[d] Returns to scale, λ, is calculated at the 3-digit industry segment level by imposing homogeneity of degree λ to input demand equations when estimating a translog production function.

[e] Other segments' productivity (and returns to scale) are weighted averages of the firm's other segment(s) weighted by the segment(s) sales.

[f] Relative industry demand is interacted with other segments' productivity and equals 1 (0, -1) when the segment's change in shipments at the industry level is greater (equal, less) than that of the firm's median segment.